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VIBRATING EMOTİONS: TECH FOR ASPERGERS'S

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VIBRATING EMOTIONS: TECH FOR ASPERGERS'S

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Approval of the Engineering Faculty

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ABSTRACT

VIBRATING EMOTIONS: TECH FOR ASPERGERS'S

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Bachelor of Science, Department of Mechanical Engineering

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This thesis offers a novel method to help people with Asperger syndrome—a disorder sometimes marked by difficulties identifying and understanding emotional cues in social settings. Asperger syndrome sufferers may find it difficult to categorize emotions such happiness, sorrow, or rage, which might cause problems in social situations and influence general quality of life. The main goal of this work is to solve these difficulties by means of a system including three fundamental technologies: Computer Vision (CV), Machine Learning (ML), and Internet of Things (IoT). These disciplines taken together provide a strong basis for building an adaptive, real-time model intended to precisely identify and interpret human face emotions.

Using computer vision methods, the suggested system detects and analyzes facial signals, therefore recognizing minute variations in expression corresponding to particular emotions. Trained on several facial expression datasets, machine learning techniques then categorize

these expressions as either positive or negative. This categorization sets off an IoT-enabled feedback system whereby vibration signals are delivered to two specifically made bracelets: one bracelet vibrates to indicate happy feelings and the other to indicate negative emotions. The technology provides instantaneous, simple insights by immediately giving the user this haptic input that can assist those with Asperger syndrome in better understanding and handling of social cues.

For those with Asperger syndrome, this wearable tool might improve emotional understanding and boost social confidence so they may negotiate social settings more naturally. The initiative also shows how IoT, ML, and CV may be combined to provide assistive tools that support social inclusion, empathy, and communication, therefore representing a step forward in the application of multidisciplinary technologies to tackle challenging social challenges. Through advancing knowledge of human emotions in an original manner, this study offers insightful analysis of how technology may be used to assist neurodiverse people.

Keywords: Machine Learning, Computer Vision , Internet Of Things

ÖZ

BİTİRME PROJESİ RAPORU YAZMANIN IZDIRABI: BİR TARİHÇE

TEK , Anıl Sabri

Lisans, Bilişim Sistemleri Mühendisliği Bölümü

Tez Yöneticisi: Prof. Dr.

Kasım 2020, 56 sayfa

Bu tez, Asperger sendromu olan kişilere sosyal ortamlarda duygusal ipuçlarını tanımlamada ve anlamada yaşadıkları zorluklara yardımcı olmayı amaçlayan yenilikçi bir yöntem sunmaktadır. Asperger sendromu olan bireyler mutluluk, üzüntü veya öfke gibi duyguları sınıflandırmakta zorlanabilir; bu da sosyal etkileşimlerde sorunlara yol açabilir ve yaşam kalitesini etkileyebilir. Bu çalışmanın temel amacı, bu zorlukları çözmek için Bilgisayarla

Görü (CV), Makine Öğrenimi (ML) ve Nesnelerin İnterneti (IoT) gibi üç temel teknolojiyi içeren bir sistem geliştirmektir. Bu disiplinler bir araya gelerek, insan yüz ifadelerini gerçek zamanlı olarak doğru bir şekilde tanımlayan ve yorumlayan uyarlanabilir bir model oluşturmak için güçlü bir temel sağlar.

Önerilen sistem, bilgisayarla görme yöntemlerini kullanarak yüz ifadelerini algılar ve analiz eder, böylece belirli duygulara karşılık gelen ince farklılıkları tanır. Çeşitli yüz ifadesi veri setleriyle eğitilen makine öğrenimi algoritmaları, bu ifadeleri pozitif veya negatif olarak sınıflandırır. Bu sınıflandırma, IoT destekli bir geri bildirim sistemini tetikler; böylece, özel olarak tasarlanmış iki bileklik aracılığıyla titreşim sinyalleri iletilir: bir bileklik pozitif duyguları, diğeri ise negatif duyguları işaret etmek için titreşir. Sistem, kullanıcıya anında sağladığı bu dokunsal geri bildirimle Asperger sendromu olan bireylerin sosyal ipuçlarını daha iyi anlamalarına ve yönetmelerine yardımcı olabilir.

Bu giyilebilir araç, Asperger sendromu olan kişilerin duygusal anlayışlarını geliştirebilir ve sosyal güvenlerini artırabilir; böylece sosyal ortamlarda daha rahat etkileşim kurmalarına yardımcı olur. Proje, IoT, ML ve CV teknolojilerinin birleştirilerek sosyal içermeyi, empatiyi ve iletişimi destekleyen yardımcı araçlar oluşturabileceğini göstermekte ve çok disiplinli teknolojilerin zorlu sosyal problemlere yönelik uygulanmasında bir ilerleme olarak öne çıkmaktadır. Bu araştırma, teknolojinin nöro çeşitliliğe sahip bireyleri desteklemek için nasıl kullanılabileceğine dair değerli bir analiz sunarak, insan duygularına dair anlayışın yenilikçi bir biçimde ilerlemesini sağlamaktadır.

Anahtar Kelimeler: Bilgisayar Öğrenimi , Bilgisayarla Görme , Nesnelerin İnterneti

DEDICATION

To My Family and the ones who support me

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LIST OF ABBREVIATIONS

ML	Machine Learning
CV	Computer Vision
IoT	Internet of Things
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
SVM	Support Vector Machine
KNN	K-Nearest Neighbors
AS	Asperger Syndrome
RF	Random Forest
LBPH	Local Binary Pattern Histogram
DML	Distributed Machine Learning
CPU	Central Processing Unit
MQTT	Message Queuing Telemetry Transport
TCP	Transmission Control Protocol
YOLO	You Only Look Once
MVS	Machine Vision System

1. INTRODUCTION

People with Asperger Syndrome (AS) generally have difficulty determining facial expressions, which can lead to misunderstandings and various other problems.

Communication has many layers and components, such as gestures, facial expressions, words, eye movements, and more. In situations where people with AS do not know others well, they may respond differently than expected, as what is considered "normal" in social life might not always be clear to them. They tend to focus on the mouth rather than the eyes, even though the eyes usually convey more information. This can lead individuals with Asperger Syndrome to experience depression, and they may eventually isolate themselves from society [1].

Particularly in fields like Computer Vision (CV), Machine Learning (ML), and the Internet of Things (IoT), advances in technology have opened up fresh chances to assist people with particular neurodevelopmental needs—including those with AS. For people with AS, these technologies offer an opportunity to help with emotion recognition—a major problem. For example, computer vision helps machines to real-time evaluate and understand visual data including facial expressions. Conversely, machine learning lets systems "learn" from data and over time improve accuracy, hence strengthening the system's capacity to identify minute emotional signals. IoT enables wearable gadgets to interact naturally with other technologies by helping connectivity between devices.

People with AS frequently struggle to identify facial expressions and gestures, as seen in [1], which can lead to mental health difficulties and misunderstandings and drive them to distance themselves from others. With the use of technologies like CV , ML, IoT, this work intends to create a system that can enable persons with AS in identifying emotions, therefore enabling them to comprehend or address these difficulties. The ML model will identify the emotions transmitted via CV using visual data while the device operates in real time. IoT will lastly allow this output to be converted into a command transmitted to a pair of wristbands. These bracelets will depict both good and bad feelings. Basically, this approach seeks to enable people with AS to engage more boldly in daily life by making social events more accessible and pleasant for them.

2. LITERATURE REVIEW

There is a research aims to label the emotions of people with Asperger Syndrome (AS) while they are engaged in learning activities, using different types of machine learning algorithms, specifically CNN (Convolutional Neural Network) and LSTM (Long Short-Term Memory). In this study, CNN is used to detect facial expressions and gestures, categorizing them into distinct emotional labels. According to the results, CNN performed well, achieving an accuracy of 90.06%. The output from CNN is then passed to LSTM, which analyzes these outputs over time to detect current emotions based on past patterns. LSTM aims to find correlations and trends in emotional states, helping to capture the flow of emotions in a continuous learning environment [2]. Furthermore, Computer Vision is a constantly evolving field. As seen in [2], a model called AlexNet, a variant of CNN, achieved an accuracy of 84.96% in correctly labeling emotions, highlighting CNN's advantage over other methods like Support Vector Machine (SVM), LSTM, and K-Nearest Neighbors (KNN). Despite CNN's strength, there are still challenges with this model. According to a 2019 article in Nature [3], varying poses remain difficult for CNN models to recognize and label accurately. However, as technology advances each year, significant improvements are being made, and results continue to improve.

In a study where the purpose is forest characterization and carbon monitoring ,forest segmentation, tree species classification, and biomass estimation CV methods are being used are Random Forest (RF) , SVM , kNN , CNN , Gradient Boosting and XGBoost this algoritms RF Used for classification and regression in forest mapping due to its robustness in handling varied data from remote sensing images. SVM Effective in species classification; excels in tasks where class boundaries are clear. kNN Suitable for simpler classifications with well-separated classes, used for interpretability. CNNs Ideal for detailed image segmentation, such as forest mask generation, due to their high accuracy in spatial feature extraction. Gradient Boosting and XGBoost Employed for regression tasks like biomass estimation, improving accuracy with sequential learning on complex datasets.

In forest monitoring, deep learning models, particularly CNNs, outperform traditional machine learning approaches in tasks requiring high spatial precision, such as segmentation and complex classification. RF and SVM are still widely used for less computationally

intensive tasks or when model interpretability is needed. The advancements in CNN models and ensemble learning techniques like Gradient Boosting indicate a strong trend towards integrating high-capacity deep learning for accurate forest characterization and resource monitoring[4].

A UAV (Unmanned Aerial Vehicle)-based early forest fire detection model that uses technologies like deep learning, sensor fusion, and data augmentation is essential because wildfires have a significant impact on agricultural activities and more [5]. Moreover, countries like Canada, Australia, and the United States have a bad history with large and destructive wildfires [6], [7], [8]. In the United States, it is noted that 85% of the wildfires that occurred between 1992 and 2015 were caused by humans, while the remaining 15% were due to natural causes .

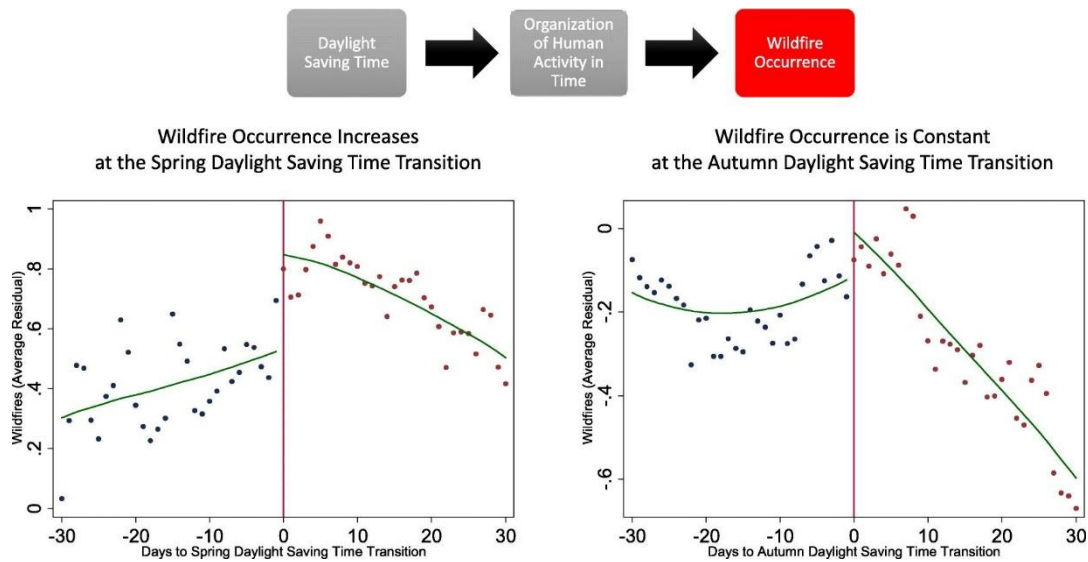


Figure 2.1: Wildfire Occurrence [9]

Therefore, a UAV-based system capable of detecting wildfires is more efficient than sending a crew for detection. This system allows users to allocate their manpower more efficiently .

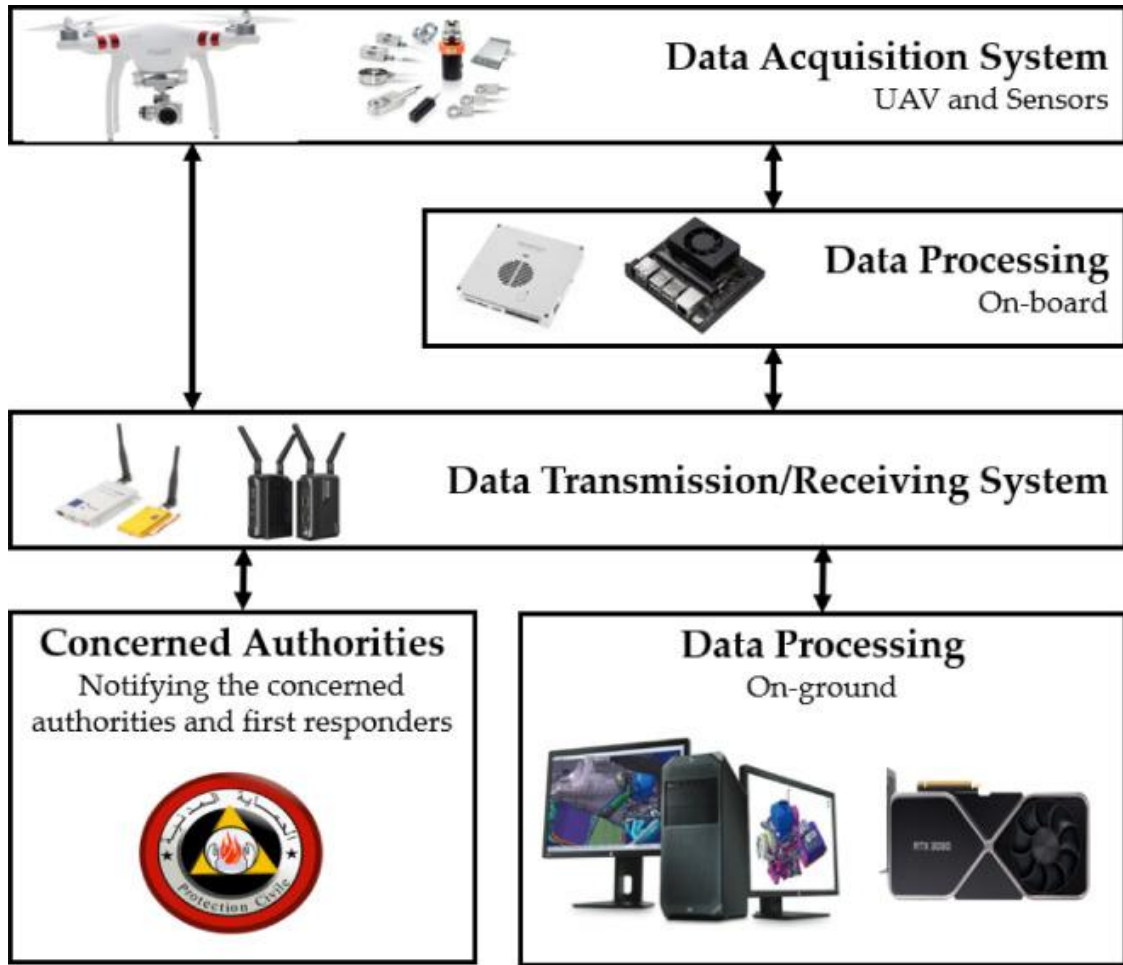


Figure 2.2: UAV-based remote sensing system flowchart for forest fire detection and concerned authorities' notifications [5]

It is reasonable to assert that deep learning methods for wildfire detection exhibit varying strengths when we compare the methods currently in use and draw a conclusion. Image classification models, including GoogLeNet, are capable of achieving high accuracy (up to 99%). However, their efficacy in detecting small or obscured fires is restricted by their difficulty with localization. Object detection methods, particularly YOLO variants, are highly effective in both classification and localization. For example, YOLOv2 accomplishes an F1-Score of 99.14% and 6 FPS, while YOLOv3-SPP achieves a mAP of 97.81%, rendering them appropriate for real-time applications. Strong accuracy is provided by a faster R-CNN, which

necessitates a greater amount of computational capacity, with F1-Scores of approximately 71.5%. Advanced techniques, such as LSTMs, can achieve temporal data accuracy as high as 99.89%; however, their complexity restricts their integration with UAVs. Overall, YOLO-based object detection methods offer the optimal combination of speed and precision for real-time, practical wildfire detection, particularly in dynamic environments [5] .

The development of smart assistance systems, like the Smart Mirror, provides tailored support for individuals with Asperger Syndrome by integrating technologies such as Raspberry Pi, OpenCV, and SQLite. Using Viola-Jones for face detection and Local Binary Pattern Histogram (LBPH) for face recognition, the system captures user images and displays personalized daily tasks and contextual updates. This reduces dependency on caregivers, offering greater independence. Unlike general-purpose smart mirrors, this system focuses on neurodivergent users' specific needs. While it demonstrates effective use of affordable hardware and robust algorithms, future improvements could include voice controls and enhanced scalability for broader applicability [10].

Emerging as a reasonably affordable substitute for training ML models on resource-limited platforms is Distributed Machine Learning (DML). In this work, CNNs on the CIFAR-10 dataset are trained using a 4-node Raspberry Pi cluster. It shows using data-parallelism and Docker-based settings that adding nodes lowers training times but with declining yields due of communication expense. Rising Central Processing Unit (CPU) core counts revealed more consistent speedup free from overhead problems. Although the cluster efficiently serves low-complexity activities, scalability only spans 4–5 nodes.

By offering a low-cost, easily available ML training approach, the paper offers a fresh contribution to the body of knowledge. Unlike conventional high-performance configurations, this method lets institutions with minimal resources, independent researchers, and students apply machine learning environments. The results show that early-stage experimentation, proof-of-concept testing in ML, and practical tool for educational reasons Raspberry Pi clusters can be used. By providing a substitute for costly hardware for non-intensive activities, this study shows DML's ability to democratize access to machine learning [11].

This another study employs Node-RED, Message Queuing Telemetry Transport (MQTT), and Modbus Transmission Control Protocol (TCP) protocols on a Raspberry Pi 4B platform to create a web-based, cross-platform system. By managing lighting, air conditioning, and curtains, the system simplifies control, reduces energy consumption, and supports remote monitoring across devices. The findings demonstrate the practicality of low-cost IoT setups for enhancing energy management and equipment usability in academic and industrial settings [12].

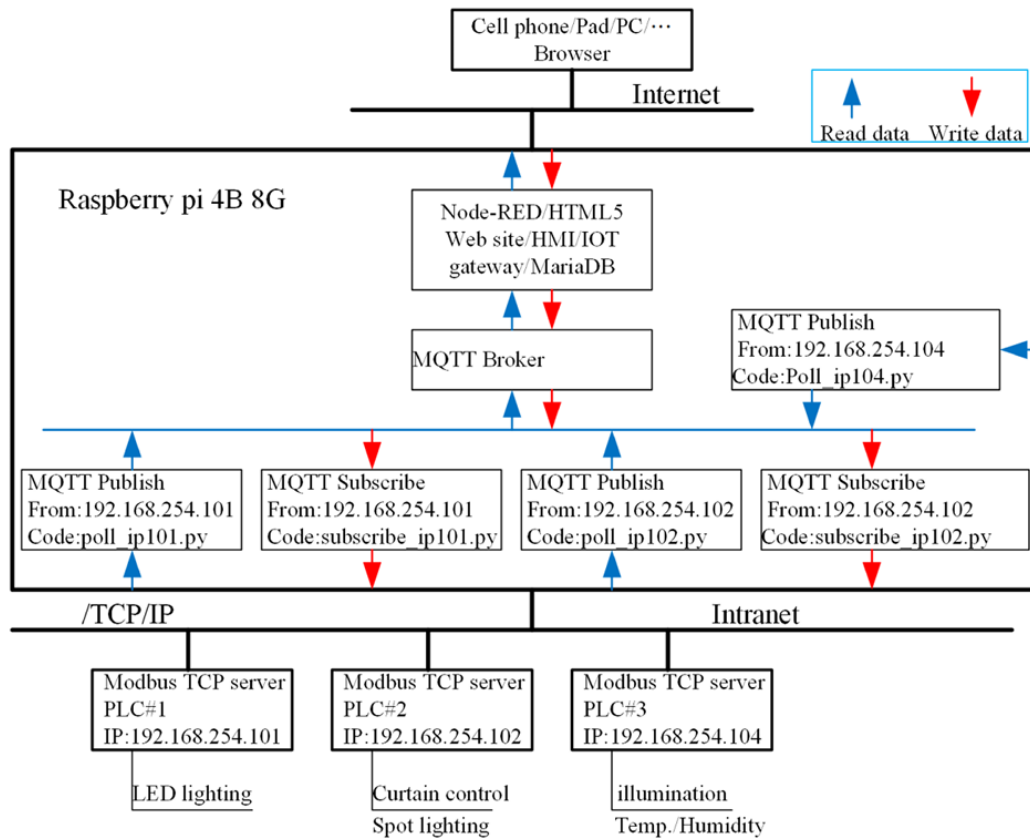


Figure 2.3: Control system software architecture [12]

The system architecture, as shown in **Figure 2.3**, centers on a Raspberry Pi 4B, integrating Node-RED, MQTT, and MariaDB for communication and data management. Using MQTT Publish/Subscribe, the Raspberry Pi interacts with Modbus TCP servers linked to PLCs: PLC #1 controls LED lighting, PLC #2 manages curtains and spotlights, and PLC #3 monitors temperature, humidity, and illumination. The system enables efficient local communication via the intranet and remote monitoring through a web interface, showcasing scalability and real-time control [12].

Within the context of food processing, this study studies the application of machine vision and deep learning with the goal of enhancing both efficiency and food safety. The objective is to automate processes such as quality evaluation, grading, and the identification of alien objects while reducing the amount of errors that are caused by human intervention. Machine vision systems (MVS) make use of sophisticated imaging methods such as hyperspectral, X-ray, and thermal imaging, in addition to algorithms that range from traditional machine learning (for example, support vector machines and kernel neural networks) to deep learning models like convolutional neural networks and You Only Look Once (YOLO). As a result of the findings, deep learning is superior to conventional approaches in terms of accuracy and real-time processing. This enables exact classification, defect identification, and non-destructive food testing. These advancements address issues raised by the industrial sector while ensuring that quality and safety are preserved throughout the food manufacturing process [13].

3. COMPUTER VISION , MACHINE LEARNING AND INTERNET OF THINGS

This section will examine closely the ideas of CV, ML, and IoT and how they interact to solve problems experienced by people with AS. Emerging as transforming tools in modern invention, these technologies are revolutionizing sectors including healthcare, communication, and assistive systems. The historical development of these ideas, their technological relevance, and their special benefits in producing an adaptive emotional detection system will be discussed in this part of the section.

3.1 Machine Learning

ML has developed from its early beginnings in cybernetics and control science to become a cornerstone of modern artificial intelligence. Emerging with models like Rosenblatt's Perceptron in the late 1950s, inspired by human neural systems, ML laid its foundations in neural network research. Despite early challenges, including criticisms of perceptron limitations in the 1960s, the field experienced significant growth with the introduction of backpropagation and the rise of big data in the 21st century. Today, ML enables complex data-driven solutions across industries, powered by advancements in computational capabilities and deep learning techniques [14].

3.1.1 Data And Features

ML relies on structured datasets composed of data points, each described by features that may be categorical (e.g., gender), ordinal (e.g., stages), or numerical (e.g., test results). These features combine into a feature vector, positioning each data point in a multi-dimensional space. As datasets become complex, dimensionality reduction techniques help identify patterns effectively. Proper data handling and well-designed features are key to ML success . [15].

3.1.2 Supervised And Unsupervised Learning

To effectively solve problems using machine learning, there are four key steps to follow:

- A. First, clearly define the features of the problem.
- B. Second, select the most suitable algorithm for the task.
- C. Third, train the data model and evaluate its efficiency.
- D. Finally, use the trained model for forecasting or predictions.

There are various methods that can be applied within a machine learning model, two of the primary approaches being supervised and unsupervised learning [16].

Supervised learning is a type of machine learning where an algorithm learns from a labeled dataset containing input-output pairs. The algorithm develops a mathematical model by analyzing these pairs, using the inputs to predict the corresponding outputs. During the training process, the algorithm compares its predictions to the predefined outputs, adjusting the model to improve accuracy. This iterative process enables the algorithm to generalize patterns in the data and apply them to unseen inputs. Supervised learning is primarily used for tasks such as classification and regression. Classification involves categorizing data into predefined classes, while regression predicts continuous values based on input variables [16].

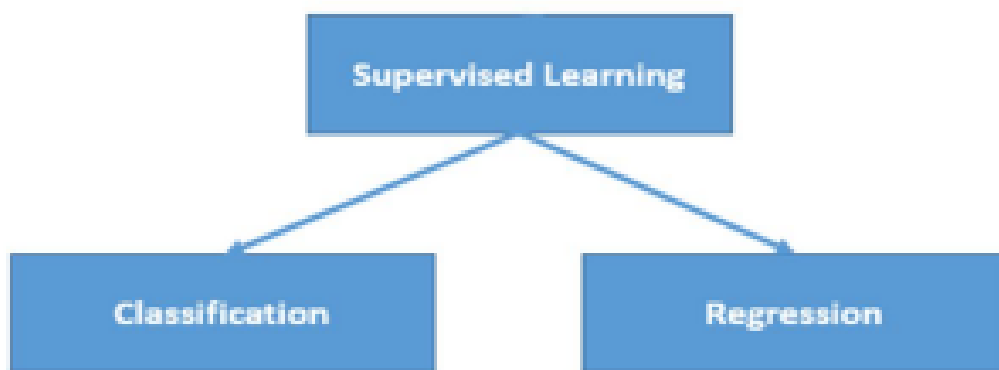


Figure 3.1: Supervised Learning

Unsupervised learning is a machine learning approach used to uncover patterns and structures in unlabeled data. Techniques such as clustering and dimensionality reduction help identify relationships and reduce complexity in high-dimensional datasets. Clustering methods, like k-

means and density-based clustering, group similar data points without predefined labels, while dimensionality reduction techniques, such as PCA and t-SNE, simplify data visualization and improve model efficiency by retaining essential variability. These methods are particularly valuable in exploratory data analysis, enabling the discovery of meaningful insights in complex datasets [15] .

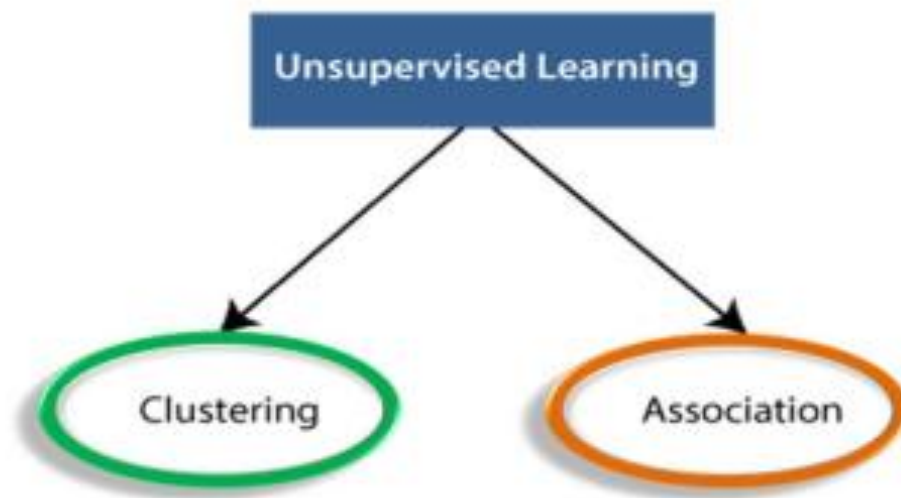


Figure 3.2: Unsupervised Learning

Supervised and unsupervised learning are two fundamental methods in machine learning, each with distinct purposes and approaches. The primary difference lies in the presence of labeled data. Supervised learning requires labeled input and output pairs, enabling the system to learn the mapping between them. In contrast, unsupervised learning deals with unlabeled data, focusing on uncovering patterns and structures within the dataset without predefined outputs.

Key differences:

Data Labeling: Supervised learning uses labeled data, while unsupervised learning works with unlabeled data, relying on the data's inherent characteristics.

Complexity: Supervised learning is generally less complex compared to the more challenging unsupervised learning methods.

Analysis: Supervised learning often involves offline analysis, whereas unsupervised learning is better suited for real-time analysis.

Accuracy: Supervised learning tends to produce more accurate and reliable results, whereas unsupervised learning yields moderately reliable outcomes.

Applications: Supervised learning is used for classification and regression tasks, while unsupervised learning addresses clustering and association rule mining problems [15].

To get a better visual perspective we can see the difference in Figure 3.3

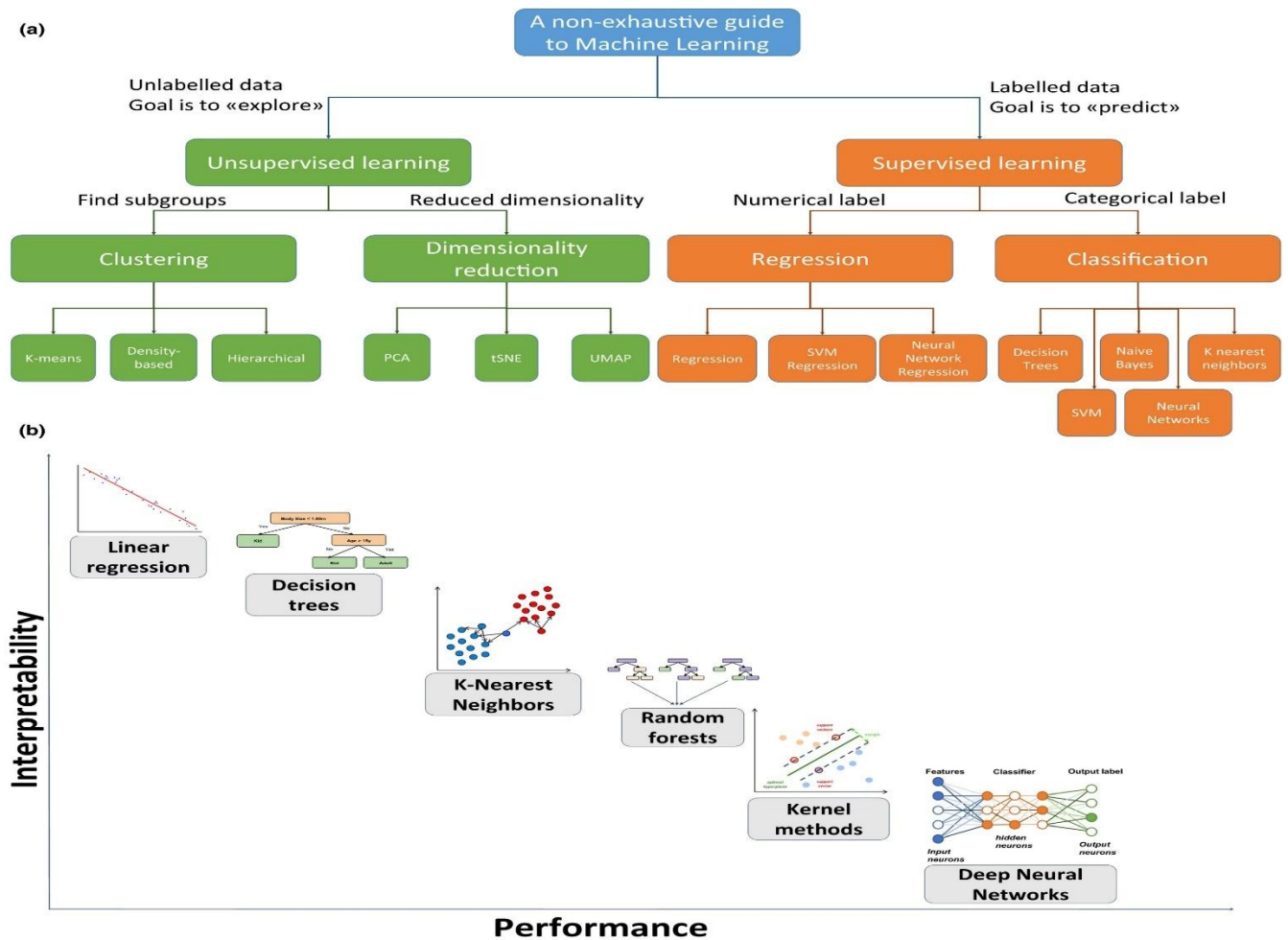


Figure 3.3: Taxonomy and overview of main machine learning (ML) algorithms [15].

3.1.3 Train-Test Split

The train-test-split is a crucial concept in ML used for to evaluate the performance and generalizability of predictive models . In this approach datasets are divided into two subsets : The training set is the set that being used for the training part of the model and the test sets are used for to test models performance based on the unseen data in test sets the split percentage must be chosen carefully because this act cause two different scenarios named Overfitting and Underfitting . Overfitting where model performs exceptionally well on training set but fails to generalize unseen data in the other hand Underfitting is where the model fails to capture the underlying patterns of the data [15]

Overfitting occurs when a machine learning model learns both the true patterns and the random noise in the training data, leading to poor performance on unseen data. This typically happens in highly flexible models, such as artificial neural networks, where the model complexity exceeds the capacity of the training data. Regularization methods, like limiting model complexity or using dropout, help prevent overfitting by reducing the model's tendency to overadapt. Conversely, underfitting arises when the model is too simple or the training data is insufficient, failing to capture the underlying patterns. This results in poor performance on both training and test data. Addressing underfitting requires increasing dataset size, improving its representativeness, or using more complex models. Achieving a balance between bias and variance is critical to avoid these pitfalls and ensure that the model generalizes well to new data [17]. We can take a closer look the difference between underfittin and overfittin in Figure 3.4

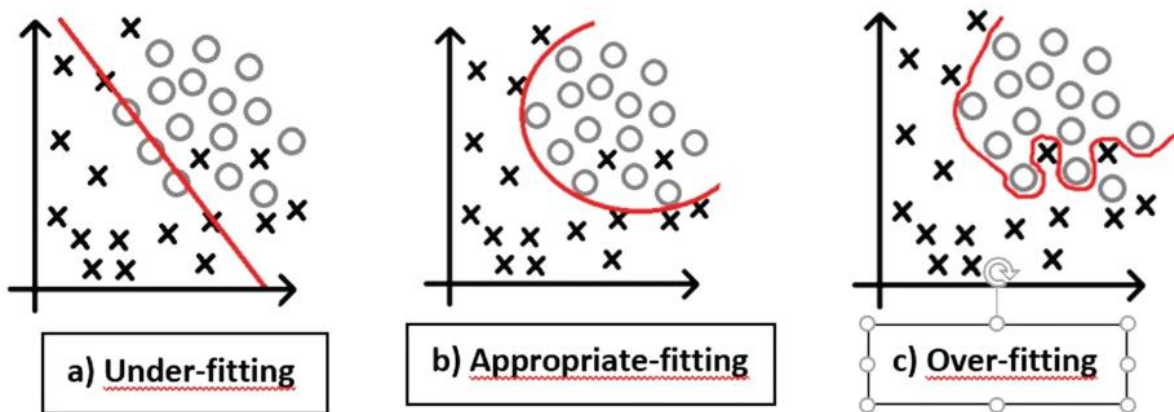


Figure 3.4: Schematic illustration of Under-fitting , Appropriate-fitting and Over-fitting

3.1.3

4. GANTT CHART

5. MATERIALS AND METHODS

6. CONCLUSION

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APPENDICES

If necessary, the special information used (user manual, codes, theoretical proofs, large schematic diagrams etc.) can be given in the appendix section.

P.S. : “PRU Thesis Manual” should be taken into consideration during the thesis writing phase

TURKISH SUMMARY

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Example: Gantt Chart

Work Package/ Description	Weeks													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Literature Review and Research														
Work Package-1														
Work Package-2														
Work Package-3														

Conclusion														
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